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Logic-Based Reverse Analysis: A Covid-19 Surveillance Data Set Classification Problem

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Abstract: This study focuses on the application of formal logic systems to real-world problem-solving, specifically in the classification of the COVID-19 Surveillance Data Set (CSDS). The research introduces the integration of a random three satisfiability problem of Boolean logic into a Hopfield Neural Network (HNN) to obtain an optimal representation of Random kSatisfiability for CSDS classification. The primary goal is to utilize the optimization capabilities of the Lyapunov energy function in the HNN to extract logical relationships and identify significant features contributing to COVID-19 detection. The CSDS used in this study is sourced from the reputable UCI dataset, and the HNN's energy minimization mechanism is employed for logical mining. Computational simulations are performed with varying numbers of clauses to validate the efficacy of the proposed model in training the CSDS for classification purposes. The results showcase the efficiency and robustness of employing reverse analysis using k-satisfiability in conjunction with a Hopfield Neural Network. This approach successfully extracts dominant features related to the logical framework underlying the CSDS. By combining formal logic systems with the power of neural networks, this research offers insights into the correlation between logical rules and COVID-19 detection. The findings contribute to our understanding of how the HNN can effectively learn and classify data, opening avenues for enhanced classification techniques in the healthcare sector and other domains.

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INTRODUCTION

The global impact of the Covid-19 pandemic has had devastating consequences on public health and well-being. Effectively identifying and isolating individuals affected by the virus has become a critical challenge. In the field of clinical medicine, significant progress has been made through the utilization of CT imaging for Covid-19 detection. CT scans have proven to be valuable in identifying anomalies that indicate the presence of the infection and provide insights into the severity of the illness, enabling informed decision-making (Suppawittaya et al., 2020; Tabish, 2020).

In recent times, various deep learning techniques have emerged as promising approaches for identifying Covid-19 cases. However, these techniques face a significant obstacle in achieving high classification accuracy due to the limited availability of training data and annotations. Furthermore, the inherent limitations of CT scans, such as poor contrast, present challenges for deep learning model systems. Ambiguous and imprecise information, particularly in pixel regions near boundaries and images associated with Covid-19 cases, can be difficult for these systems to comprehend.
Addressing the challenges associated with accuracy and reliability in deep learning-based classification systems for Covid-19 detection is of utmost importance. To overcome the limitations posed by CT scans and improve the performance of these systems in accurately identifying and diagnosing Covid-19 cases, several advancements are necessary. These include improvements in data availability, annotation, and image interpretation techniques.

In our research, we recognize and appreciate the invaluable contribution of the research community's open-source Covid-19 dataset. This dataset serves as a crucial resource for training and evaluation, fostering collaboration and progress in the global fight against the pandemic. To develop a robust and accurate classification system for Covid-19 cases, we aim to leverage the power of deep learning techniques, belief functions, and semi-supervised learning. By combining these approaches, we strive to enhance the capabilities of healthcare professionals in effectively identifying and managing the disease. Ultimately, this will lead to improved outcomes and a greater ability to control the spread of the virus. It is important to acknowledge the relevant studies that have contributed to the field, such as (Chiroma et al., 2020; Elaziz et al., 2020; Roberts et al., 2021). Their research has provided valuable insights and paved the way for advancements in Covid-19 classification systems.

Artificial neural networks (ANN) have emerged as a valuable tool in various fields such as image identification(Li, 2022), speech recognition(Oruh et al., 2022), financial forecasting (Abubakar & Sabri, 2022; Hamza & Sabri, 2022), Insurance (Abubakar & Sabri, 2023), machine translation(Pérez-Ortiz et al., 2022), and medical diagnosis (Akbarian et al., 2023). Their fault-tolerant properties make them particularly well-suited for these applications. Machine learning approaches, including ANN, offer a significant advantage in processing complex data inputs. One of the key strengths of ANN is its ability to learn from sample datasets, enabling it to adapt and improve over time. ANN is commonly used for optimization, forecasting, and random function approximation tasks. This is because these networks aim to replicate the capabilities of the human brain and nervous system, which makes them suitable for handling complex and nonlinear data patterns.

In recent times, ANN has gained prominence in the field of machine learning algorithms (MLA), serving as a versatile tool for various applications across different domains. Its ability to process and analyze large datasets, extract meaningful patterns, and make accurate predictions has made it a valuable asset in numerous areas of research and industry (El-Kady et al., 2023; Kaddoura et al., 2022; Oruganti et al., 2023). ANN has also found applications in medical research and healthcare. It has been utilized in disease diagnosis, prediction, and detection by analyzing the effects on patient development (Abubakar & Idris, 2023; Ogundokun et al., 2022; Sawhney et al., 2023). For instance, ANN has been employed in predicting fibrosis and cirrhosis, two conditions affecting the liver. By analyzing relevant patient data, such as medical history, genetic factors, and test results, ANN can provide insights into the likelihood of fibrosis or cirrhosis development(Ghazal et al., 2022; Sinha et al., 2022; Yip et al., 2023).

Additionally, ANN has been valuable in predicting the response to therapy in patients with hepatitis. By analyzing various factors such as patient demographics, viral load, treatment history, and genetic markers, ANN can help identify patients who are likely to respond positively to specific therapies. This information can aid healthcare providers in designing personalized treatment plans and optimizing patient outcomes. The use of ANN in medical approaches holds promise for improving disease management, enhancing diagnostic accuracy, and enabling targeted treatment strategies. By leveraging the capabilities of ANN, researchers and healthcare professionals can gain deeper insights into complex diseases, leading to more effective interventions and better patient care (Ibrahim et al., 2005; K et al., 2018; J. Tang et al., 2019; Vijayarani et al., 2015).

A study in (Shahid et al., 2019) discusses uses and applications of ANN the health care industry for diseases diagnostics problems. According to the study in the recent time, ANN model framework has increasingly being utilized to influence various decision making health care management. The review analyzes major aspects and drivers of ANN market acceptance in order to guide future use of this technology. Similarly, ANN has been use in artificial intelligence techniques (AI) and various algorithms modelling used in a variety of industries, various purposes including self-driving automobiles, face recognition, and disease detection and or diagnosis in health care. The study discovered that artificial intelligence is used to address many real-world conundrums. The proposed algorithm's main goal is to accurately forecast misclassified malignant tumours based a ANN model framework was proposed in (Suresh et al., 2020). ANN has also been use in prediction as presented in a study published in (Zhu et al., 2021). It studied the protein degradation and quality variations in dry-cured ham processing, and then developed using back propagation-artificial neural networks (BP-ANN) models. The results revealed the a high potentially of the BP-ANN in predicting several quality characteristics.

In the work of (Alwan & Abualkishik, 2021) an ANN model framework demonstrated the functional capability of identifying and classifying PV defects. A deep convolutional neural networks (DCNN) model was proposed in (D. Tang et al., 2021). The purpose was in reducing the association between endoscopists' endurance of effort and diagnostic accuracy. An AI-assisted system was developed and proved to be effective for novice endoscopists to obtain diagnostic performance comparable to specialists. A study (Dinaharan et al., 2022) describes the use of an ANN to estimate the wear rate of surface composites manufactured utilizing a solid-state technology. With the help of observed microstructures, the projected patterns were explained and the influence of the relevant elements was studied. The B4C-reinforced surface composite had a decreased wear rate. A computational model was developed in (Abubakar et al., 2022) based on Hopfield neural network (HNN) and satisfiability problem. The study utilized Ants Colony Optimzation Algorithm (ACO) to optimize the learning process of HNN for better classification problem of agricultural soil fertility data set (ASFDS).

To enhance model classification performance, a unique approach was devised by merging Random maximum kSAT with HNN, resulting in a novel logical rule (Abubakar, H., & Shafiq, 2022). In another investigation, ANN was combined with a novel election algorithm to expedite the training and testing stages of the model, aiming to improve classification accuracy (Abubakar, 2022). The objective of these studies was to integrate the optimization capabilities of Hopfield neural network (HNN) with random maximum kSatisfiability (MAX-RANkSAT), achieving an optimal representation in the process. By leveraging the strengths of these different techniques, the researchers aimed to enhance the performance and efficiency of the classification model.

In recent data mining studies, various artificial neural network models have emerged, including HNN, FFNN, DBFNN, KNN, CNN, and other machine learning (ML) tools, which facilitate logic mining (LM) through the extraction of knowledge (Alzaeemi & Sathasivam, 2021). These ANN models have found extensive applications in artificial intelligence (AI) and machine learning (ML) fields, particularly in data mining for diverse areas such as medical science, engineering, and industry (Alzaeemi & Sathasivam, 2021). Logic mining plays a pivotal role in extracting meaningful information from databases or datasets, and it has been demonstrated that knowledge can be effectively represented in logical or symbolic forms (Sathasivam & Wan Abdullah, 2011).

The field of data mining has witnessed the emergence of several artificial neural network (ANN) models, including HNN, FFNN, DBFNN, KNN, CNN, and other machine learning (ML) tools. These models have played a crucial role in logic mining (LM) by enabling knowledge extraction [1]. Their wide-ranging applications in AI and ML have significantly impacted data mining across various domains such as medical science, engineering, and industry (Abubakar, H., & Shafiq, 2022; Abubakar et al., 2022; Alzaeemi & Sathasivam, 2021).

The extraction of meaningful information from databases or datasets, known as logic mining, is facilitated by ANN models that effectively represent knowledge in logical or symbolic form (Sathasivam & Wan Abdullah, 2011). Among these models, Hopfield Neural Networks (HNNs) have demonstrated their efficacy in logic mining tasks. By employing recurrent neural network principles, HNNs can model complex relationships and dependencies within data, making them suitable for extracting logical relationships (Alzaeemi & Sathasivam, 2021).

Another widely used ANN model in logic mining is the Feedforward Neural Network (FFNN), which comprises interconnected layers of nodes. FFNNs excel in learning intricate mappings between input and output data, enabling the extraction of logical rules and patterns from datasets (Alzaeemi & Sathasivam, 2021).

Deep Belief Neural Networks (DBFNNs) have also garnered attention in logic mining research. DBFNNs employ unsupervised learning to pretrain multiple layers of neurons, followed by supervised fine-tuning. This hierarchical learning approach allows DBFNNs to capture complex patterns and representations, making them well-suited for logic mining with large and intricate datasets(Alzaeemi & Sathasivam, 2021).

In addition to ANN models, other machine learning tools like K-nearest neighbors (KNN) and convolutional neural networks (CNN) have been employed in logic mining. KNN algorithms effectively identify patterns and similarities in data, making them valuable for classification and clustering tasks in logic mining. CNNs, on the other hand, have revolutionized image processing and analysis by automatically learning hierarchical features from input data, thereby enhancing logic mining tasks (Sathasivam, S.; Abdullah, 2011)(Bukov et al., 2018)(Hamadneh et al., 2012)involving visual or spatial data (Alzubaidi et al., 2021).

The integration of artificial neural networks, including HNN, FFNN, DBFNN, KNN, CNN, and other machine learning tools, has significantly advanced logic mining in various domains. These ANN models facilitate the extraction of meaningful knowledge from databases or datasets, enhancing decision-making and providing valuable insights. Logic mining, with its representation of knowledge in logical or symbolic forms, further augments the applicability of ANN models. Ongoing research efforts continue to explore and refine the capabilities of ANNs in logic mining, paving the way for extracting valuable insights from complex data(Khosravi Babadi, 2023).

In order to drive progress in the field of data mining, experts from diverse disciplines such as artificial neural networks, mathematics, artificial intelligence, machine learning, and statistics come together to forge innovative data mining techniques firmly rooted in logical principles. This collaborative effort aims to push the boundaries of knowledge and empower researchers and practitioners to extract valuable insights from complex datasets.

By combining the expertise and perspectives of these different disciplines, researchers can harness the power of artificial neural networks to uncover patterns, relationships, and trends within data. The mathematical foundations and logical principles serve as the guiding framework for the development of sophisticated data mining methodologies that are both effective and reliable.

The integration of artificial intelligence and machine learning techniques further enriches the data mining process by enabling automated decision-making, predictive modeling, and pattern recognition. Statistical methods provide a robust foundation for analyzing data, validating results, and quantifying the significance of findings.

This collaborative approach not only enhances the effectiveness and efficiency of data mining techniques but also fosters interdisciplinary knowledge exchange and innovation. By leveraging the strengths of each discipline and embracing logical principles, researchers can unlock the full potential of data mining and drive advancements in various fields, including healthcare, finance, marketing, and more.. This study specifically focuses on enhancing data mining methods by integrating Random kSatisfiability (RANkSAT) propositional logic into a comprehensive model tailored for real-world applications. The model of choice is the Artificial Neural Network (ANN), which is renowned for its structured approach involving training and testing phases. ANNs have demonstrated their effectiveness in pattern recognition and extracting valuable insights for solving practical problems.

By incorporating RANkSAT logic into the ANN model, the researchers aim to augment its data mining capabilities. This logical framework provides a robust basis for addressing complex real-life scenarios. The combination of ANN and RANkSAT holds tremendous potential for improving the efficiency and accuracy of data mining processes, enabling more effective pattern recognition and information extraction in real-world applications.

Hence, the aim of this research is to enhance the capabilities of Artificial Neural Networks (ANNs) by integrating a recurrent Hopfield Neural Network (HNN), enabling the representation of logical rules within neural networks and facilitating optimal classifications for real-world problems. The utilization of Random kSatisfiability (RANkSAT) based on propositional logic is proposed as a suitable symbolic approach for mapping logical rules within neural networks. This approach simplifies the complexity of discovering relationships between variables by focusing on a maximum of three literals per sentence, making it beneficial for the classification of real-world problems. By combining ANNs and logical reasoning methods, data mining techniques become more effective, facilitating better pattern recognition and information extraction in practical applications.

In this study, a novel approach called Random k Satisfiability-based Reverse Analysis (RANkSATRA) is introduced to extract logical information from the COVID-19 Surveillance Data Set (CSDS). Previous studies have explored different perspectives on describing real data from CSDS in logical form, highlighting the utility of various HNN models for interpreting logical rules. However, there has been a gap in bridging the RANkSAT logical representation with the Hopfield neural network for COVID-19 classification. Addressing this gap is crucial as the artificial neural network algorithm can effectively handle the variations and randomness in COVID-19 analysis, offering a larger search space. Thus, this research makes the following contributions:

(a) Intelligent organization of the CSDS based on RANkSAT logical expressions.

(b) Introduction of the RANkSATRA logical rule as the primary approach to uncover hidden knowledge within the CSDS dataset and understand the relationships between its components.

(c) Evaluation of the effectiveness and accuracy of three variations of the proposed RANkSATRA logical representations for knowledge extraction from the CSDS using different numbers of clauses (NC).

To evaluate the effectiveness of the proposed approach and the utilization of logical rules within the Hopfield Neural Network (HNN) for knowledge extraction from the COVID-19 Surveillance Data Set (CSDS), performance metrics will be employed. The methodology of the HNN-RANkSATRA model for extracting logic from the CSDS dataset will be explained, highlighting its superior performance in the training stage and successful interpretation of real-life datasets to identify key factors influencing optimization problems.

The study is structured as follows: Section 2 provides a description of the materials and methods employed, including Random kSatisfiability Logic, the Hopfield Neural Network (HNN), and the Random kSatisfiability-Based Reverse Analysis Method (RANkSATRA). In Section 3, the implementation process for classifying the COVID-19 dataset is outlined. The model simulations and experimental setup are detailed in Section 4, while Section 5 presents the performance evaluation metrics. Results and discussions are provided in Section 6, followed by a section on future work and overall conclusions to conclude the study.

RESEARCH METHODS

In this section, we will outline the research methodologies utilized in this study, which can be classified into five distinct types based on their specific approaches. These methodologies encompass Random kSatisfiability (RANkSAT), the framework of the Hopfield Neural Network (HNN) model, the Reverse Analysis method based on Random kSatisfiability (RANkSATRA), the method for conducting experimental simulations of the model, and the approach for evaluating the performance of the model.

Random kSatisfiability (RAN*k*SAT)

Propositional logic encompasses the concept of Satisfiability (SAT), which involves logical rules consisting of sentences containing literals or variables. In contrast, Random kSatisfiability (RANkSAT) is a type of Boolean logic model that does not follow a systematic approach and instead incorporates a random number of clauses (NC) or literals (including negated literals) within each sentence. The application of non-systematic Boolean Satisfiability logic, specifically RANkSAT, has proven to be effective in representing simulated scenarios (Sathasivam et al., 2020).

In the context of Random kSatisfiability (RANkSAT), the process begins with a SAT where a random truth assignment is initially made. Then, a literal from an unsatisfied clause is randomly selected and set to true until that particular clause is satisfied. However, so far, no research has investigated the application of this non-systematic approach of Random kSatisfiability within discrete Hopfield Neural Networks (HNN) for solving classification problems with real-world datasets. The formulation of RANkSAT involves crucial specifications, which are described as follows:

i. A collection of attributes in form of variables $\{x_1, x_2, \ldots, x_n\}$ in a clause (C_i) . Where

$i = 1,2,3,...,n$ which comprised of a variable (x) and or its negation $(\neg x)$

ii. In this study, 3 variables are randomly chosen from the collection of attributes of n variables with equal chances of selecting a variable or its negation in each the clause.

iii. Each attributes selected i.e x_i or $\neg x_i$ in C_i is connected by a conjunction $(\wedge)$ and or disjunction $(\vee)$.

In this study, the proposed logical rule RANkSAT, employed bipolar repressentation in the form 1 or -1 such that $x_i \in \{1,-1\}$ describes the notion of TRUE or otherwise respectively in RANkSAT logical rule (Abubakar et al., 2022; Cordeiro, 2022; Medina et al., 2004). The general formulation $F_{RAN3SAT}$ is represented in Equation (1) as follows.

$$F_{RANkSAT} = \bigwedge_{i=0}^{t} C_i^{(3)} \bigwedge_{i=0}^{n} C_i^{(2)} \bigwedge_{i=0}^{m} C_i^{(1)} \qquad (1)$$

where $t,n,m \in [1,2,..k]$, $\forall t,n,m > 0$. The clause $F_{RAN3SAT}$ is defined as a random 3-SAT which consists of a clause $C_i^{(k)}$ described in Equation (2). as follows.

$$C_i^{(k)} = \begin{cases} (W_i \vee Q_i \vee A_i), k = 3 \\ (W_i \vee Q_i), \quad k = 2 \\ M_i, \qquad k = 1 \end{cases} \qquad (2)$$

where $W_i, \neg W_i$, $Q_i, \neg Q_i$, $A_i, \neg A_i$ and $M_i, \neg M_i$ in Equation (2) represent literals and their negation respectively and the first order logic is designated by $C_i^{(1)}$, $C_i^{(2)}$ is the second-order logical clauses and we denoted the third order logical clause by $C_i^{(3)}$.

This study contains a Conjunctive Normal Form (CNF) formula F_r in which all clauses are chosen uniformly, independently, and without replacement $2^r \binom{m+n}{v}$ non-trivial clauses of the length r . Note that, A_i exists in the $C_i^{(k)}$, if the $C_i^{(k)}$ contains either A_i or negation $\emptyset A_i$. The mapping of $V(F_r) \to \{-1,1\}$ is called logical mapping. The Boolean value for the mapping is expressed as 1 (TRUE) and -1 (FALSE). In theory, the example of RANkSAT formula for $k \leq 3$ is given as.

$$F_{RAN3SAT} = (W_1 \vee \neg W_2 \vee W_3) \wedge (\neg Q_1 \vee Q_2) \wedge \neg M_1 \qquad (3)$$

According to Equation (3), $F_{RANkSAT}$ comprises of equation (4)-(6) as follows.

$$C_i^{(3)} = (W_1 \vee \neg W_2 \vee W_3) \qquad (4)$$

$$C_2^{(2)} = (\neg Q_1 \vee Q_2) \qquad (5)$$

$$C_1^{(1)} = \neg M_1 \qquad (6)$$

Therefore, the outcome of Equation (3) is satisfied if Equations (4)-(6) are satisfied. i.e

$$C_i^{(3)} = C_1^{(2)} = C_2^{(1)} = 1 \qquad (7)$$

This research aims to integrate RANkSAT into the proposed Hopfield Neural Network (HNN) model using the reverse analysis technique for COVID-19 data classification. By incorporating the RANkSAT logical rule, the modified networks will be able to reveal the accurate patterns and behaviors of the utilized datasets.

Hopfield Neural Network (HNN)

A Hopfield network is a neural network architecture characterized by a single layer of interconnected recurrent neurons. These neurons are fully connected, allowing for information to flow bidirectionally within the network. By establishing a connection between the cost function and the energy function, the Hopfield network can effectively address optimization problems involving tightly interconnected neurons. This can be used to optimize a given optimization problem. If there are two neurons i and j, then a symmetric connection weight T_{ij} exists between them. "The Hopfield network is an RNN with symmetric links." Other RNNs that are not Hopfield networks include fully reconnect, recursive, Elman, Jordan, and others. The Hopfield network employs two types of operations in its associative memory: auto-association and hetero-association. Auto-association involves connecting a vector with itself in the memory storage, while hetero-association involves linking two distinct vectors in the memory storage. These operations play a crucial role in addressing a wide range of optimization and combinatorial tasks. In the Hopfield neural network (HNN), organized neuronal states are represented by Ising variables. The discrete HNN utilizes neurons in a bipolar form of representation, where each neuron is assigned a value of either 1 or -1. (Uykan, 2020)- (Sathasivam, 2009). Equation (4) depicts a basic summary of neuron state firing in HNN.

$$S_i = \begin{cases} 1 \quad , \ if \ \sum_j T_{ij} S_j < \delta \\ -1 \ , \ Otherwise \end{cases} \qquad (8)$$

where T_{ij} is the synaptic weight vector from the neuron j to neuron i . The state of neurons j and d is the is predefined setup (threshold) values S_j . The value of $\delta = 0$ has been specified in to ensure that the energy of the network decreases, the connections in the Hopfield network are designed in such a way that there are no self-connections. In other words, a neuron in the Hopfield network is not directly connected to itself. This design feature helps in optimizing the performance of the network and ensuring effective information processing.

$$T_{ijk}^{(3)} = T_{kij}^{(3)} = T_{kji}^{(3)} \qquad (9)$$

$$T_{ji}^{(2)} = T_{ij}^{(2)} \qquad (10)$$

$$T_i^{(1)} = T_j^{(1)} \qquad (11)$$

$$T_{jj} = T_{ii} = 0 \qquad (12)$$

As a result, HNN has architecturally symmetrical elements. The HNN model features detailed elements akin to the *Ising* model of magnetism . The spin points obey in the direction of a magnetic field, as the neuron state is referred to in bipolar representation $S_i \in \{1,-1\}$. This causes each neuron to flip until the equilibrium energy is reached. This leads each neuron to flip until balance is restored. Thus, it follows the dynamics $S_i \to \mathrm{sgn}[h_i(t)]$ where is the local field (h_i) of the neuron interaction.

The total field induced by each neuron is provided as in Equation (13) as follows.

$$h_i = \sum_{k}^{N}\sum_{j}^{N} T_{ijk} S_j S_k + \sum_{j}^{N} T_{ij} S_j + T_i \quad (13)$$

The role of the local field in the Hopfield Neural Network (HNN) is to analyze the final state of neurons and generate all possible logic induced by Random kSatisfiability (RANkSAT) from this state. The HNN network is known for its ability to consistently converge to stable states (Hopfield, 1982), making it a significant characteristic of the model. In the context of RANkSAT logic programming, the Lyapunov energy function (LEF) within the HNN is utilized, and its representation is presented as follows:

$$H_{F_{RANkSAT}} = \ldots - \frac{1}{3}\sum_{i=1}^{N}\sum_{j\neq k}^{N}\sum_{k=1, i\neq k}^{N} T_{ijk}^{(3)} S_i S_j S_k - \frac{1}{2}\sum_{i=1, i\neq j}^{m}\sum_{j=1}^{m} T_{ij}^{(2)} S_i S_j - \sum_{i=1, i\neq j}^{m} T_i^{(1)} S_i \quad (14)$$

The energy function of the HNN model is especially critical since it will decide the interoperability of the network. The equation's output will be checked to see if it is global or not. When the generated neurons' states approached global minimum energy, the network would create the appropriate response. There has been little work done to merge HNN and RANkSAT as a single computational network..

Random *k*Satisfiability Reverse Analysis (RAN*k*SATRA)

Reverse Analysis plays a vital role in the field of logic mining by extracting valuable logical rules from given datasets. Logic mining has become a significant area in data mining, enabling the representation of information in a logical format and facilitating the extraction of meaningful knowledge. The reverse analysis technique, which is based on the horn clause, has been utilized to extract valuable insights from real-world data. In this study, we propose a method called Random kSatisfiability enhanced Reverse Analysis (RANkSATRA) to extract the optimal RANkSATRA logical rule that explains the behavior of COVID-19 datasets.

RANkSATRA is a logic extraction method that leverages the structure of the HNN-RANkSAT model to extract valuable logical rules from the COVID-19 dataset. The flexible and convenient nature of RANkSAT makes it suitable for describing and analyzing datasets with non-systematic behavior. The RANkSATRA approach allows for the derivation of an ideal logic representation of the relationship between attributes in the COVID-19 dataset, which is beneficial for classification and estimation purposes. By uncovering hidden information within the dataset, the RANkSATRA approach enhances our hybrid HNN model and contributes to the overall data mining framework.

In the RANkSAT clauses, each attribute is translated into atoms, enabling the construction of the RANkSAT logical rule. By considering seven selected attributes from the dataset, the logical rule is formulated.

Logic mining, a technique based on the principles of logic programming theory, is employed to extract hidden knowledge from the data set. Specifically, our HNN-RANkSATRA model implements RAN3SATRA as a logic mining technique to establish the relationship of entries within the CSDS. The RANkSATRA $(k £ 3)$ may be able to disclose the level of connectivity between three neurons by gaining the synaptic weight between them.

In this study, we consider *n* attributes extracted from CSDS dataset $s_i \; Î \; [s_1, s_2, ...s_n]$. Where all entries are being represented in bipolar states i.e 1 or -1. Since this chapter considers $F_{RAN3SAT}$, the arrangement of each S_m consists of S_i, S_j, S_k where $i \neq j \neq k$. For S_m those leads $P_{RANkSAT}^{learn} = 1$ have been presented as follows

$$S_m = \left(S_i^{\max[n(s_i)]} \vee S_j^{\max[n(s_j)]} \vee S_k^{\max[n(s_k)]} \right) \quad (15)$$

$$S_i = \begin{cases} S_i, & S_i = 1 \\ \neg S_i, & S_i = -1 \end{cases} \quad (16)$$

Based on the value of S_m obtained in Equation (15), we can formulate $P_{RANkSAT}^{best}$:

$$P_{RANkSAT}^{learn} = \vee_{m=1}^{k} S_m \quad (17)$$

For example, we will choose

$$Y_1 = S_1 \vee \neg S_2 \vee \neg S_3 \quad (18)$$

If the conditions in Equation (19)-(21) holds, then $P_{RANkSAT}^{best}$ will be inserted in the HNN, and extract the states of neurons corresponding to $E_{F_{RAN3SAT}^{best}} = 0$.

$$S_1^{\max[n(S_1)]} = S_1 \quad (19)$$

$$S_2^{\max[n(S_2)]} = \neg S_2 \quad (20)$$

$$S_3^{\max[n(S_3)]} = \neg S_3 \quad (21)$$

The corresponding values of T_{ijk} is computed by equating Equation (3) to Equation (14). During the testing process, we obtained the induced logic rule, S_i^B, according to Equation (13). Subsequently, P_i^B which is the induced logic rule in HNN, will be built according to logical rule given in Equation (2). Finally, induced logic rule chosen is obtained according to Equation (22) basad on the CSDS Training data.

$$P_i^B = P_i^{test} \quad (22)$$

The logical rule "RAN*k*SATRA" is used in this experiment to discover the relationship between the data set. In learning CSDS, detected or not detected would be turned into bipolar representations 1,-1. In RAN*k*SATRA, every objective would be encoded by neurons. As a result, this data set would consider a maximum of seven neurons. CSDS entries will be used to identify each neurons state.

RANkSATRA Experimental setup

To assess the effectiveness and performance of the Random kSatisfiability reverse analysis (RANkSATRA) in controlling the learning process of the Hopfield neural network (HNN) for the classification of the COVID-19 Surveillance Data Set (CSDS), a comprehensive simulation was conducted. The dataset was divided into two subsets, with 60% of the data allocated for the learning phase and the remaining 40% for testing purposes.

The simulation was performed using Microsoft Visual C++ applications on a Windows 8.1 platform featuring a 64-bit system, a CPU with a clock speed of 4.40 GHz, 4GB of RAM, and a 400 GB hard drive. A dedicated timeframe of 24 hours of CPU time was assigned for both the learning and testing phases. This allocation ensured that the model had sufficient computational resources to complete the necessary tasks. If the model exceeded the recommended processor time limit, it would indicate that the HNN-based RANkSATRA approach faced challenges in effectively training with real-life data.

The primary objective of the simulation was to evaluate the performance of the proposed approach within the constraints of the provided computational resources. This assessment would provide valuable insights into the model's efficiency and suitability for practical implementation in real-world scenarios.

Regarding the incorporation of the Satisfiability logical rule into the HNN as a single model, previous works by Sathasivam and Abdullah utilized HORNSAT for logic mining, while the RANMAXkSAT model proposed by (Abubakar, 2020) and the RANkSAT model proposed by (Abubakar & Sathasivam, 2020)were considered as existing logic mining techniques in the research. These models provided a foundation for exploring the implementation of HNN-RANkSATRA for CSDS classification.

Implementation of CSDS

This section focuses on the classification of the COVID-19 Surveillance Data Set (CSDS) using three distinct techniques: RANkSATRA, HORNkSATRA, and RANMAXkSATRA. The CSDS dataset utilized in this study was obtained from the UCI machine learning repository, which is recognized as a reliable and comprehensive source of data for various applications.

The original CSDS dataset comprises seven instances with nine attributes, consisting of two classes: "detected" and "not detected." To identify the most relevant and influential features within the COVID-19 dataset, feature selection methods were employed. The primary objective of this experiment is to thoroughly analyze the characteristics and properties of the CSDS dataset.

Performance Evaluation metrics

In this section, a comprehensive set of simulated tests was carried out to evaluate the performance of our proposed logical rule model under different clause configurations. These tests aimed to assess the effectiveness of our SATRA model in extracting significant logical rules from the COVID-19 Surveillance Data Set (CSDS), utilizing various performance indicators.

To evaluate the performance of the Hopfield Neural Network (HNN) models during the training phase, specific metrics introduced in this study were employed. These metrics served as quantitative measures to assess the alignment between the retrieved neuron state and the optimal categorization of the CSDS. This evaluation provided insights into the effectiveness of the RANkSAT representation in controlling the network during the learning phase.

To quantify the effectiveness of the RANkSAT representation, we utilized a fitness equation that was specifically designed for this purpose. The fitness equation played a crucial role in determining how well the network adapted and learned from the CSDS dataset, thereby evaluating the model's performance. Through these simulated tests and performance evaluations, we aimed to gain a comprehensive understanding of how our proposed logical rule model, integrated with the HNN, performed under varying conditions. The results obtained from these evaluations would provide valuable insights into the model's effectiveness and its ability to extract relevant logical rules from real-world datasets such as the CSDS.

$$f_k = \sum_{k=1}^{NC} C_k \tag{23}$$

where NC is defined as the number of clauses for any given P_k^B.

C_k is defined according to Equation as follows.

$$C_k = \begin{cases} 1 & True \\ 0 & False \end{cases} \tag{24}$$

The measurements are assessed by considering accuracy and error accumulation, which indicate the complexity of the network in relation to the number of neurons. This evaluation is conducted using the following formula.

$$TRANING\_MAE = \sum_{i=1}^{n} \frac{1}{n} \left| f_{\max} - f_k \right| \tag{25}$$

$$TRAINMING\_RMSE = \sum_{i=1}^{n} \sqrt{\frac{1}{n}(f_{\max} - f_k)^2} \tag{26}$$

where $f_{\max}$ and f_k are the output value and target output value respectively, and n is a number of the iterations.

$$\text{TRAINING\_BIC} = nIn(MSE) \tag{27}$$

where n represents the number of simulation iterations, and MSE represents the measurement used to calculate BIC. Consequently, the MSE formula is provided as follows:

$$TRAINING\_MSE = \frac{1}{n}\sum_{i=1}^{n}(f_{\max} - f_k)^2 \tag{28}$$

The following is use in calculating the model accuracy in CSDS classification.

$$TRAINMING\_ACCURACY = \frac{P_{induced}^{Correct}}{N_{P_{test}}} \times 100\% \tag{29}$$

The performance of the HNN on the proposed logical rule is presented in Table 3.

RESULT AND DISCUSSION

In this study, we conduct a comparison of the simulated program for neurons in the HNN-RANkSATRA model with two existing models, namely HNN-HORNkSAT (Sathasivam, S.; Abdullah, 2011) and RANMAXkSAT(Abubakar et al., 2020), using various performance metrics. These metrics include the Bayesian information criterion (BIC), mean absolute error (MAE), root mean square error (RMSE), CPU time, and accuracy in classifying the COVID-19 Surveillance Data Set (CSDS). The MAE and RMSE values of the HNN models during the training process are visually represented in Figures 2 and 3.

In this study, we conducted a comprehensive comparison of the simulated program for neurons in the HNN-RANkSATRA model with two existing models, namely HNN-HORNkSAT(Sathasivam, S.; Abdullah, 2011) and RANMAXkSAT(Abubakar et al., 2020), using various performance metrics. These metrics included the Bayesian information criterion (BIC), mean absolute error (MAE), root mean square error (RMSE), CPU time, and accuracy in classifying the COVID-19 Surveillance Data Set (CSDS). Figures 2 and 3 visually represented the MAE and RMSE values of the HNN models during the training process.

The focus of the comparison was on the performance of different satisfiability logic variants in classifying the CSDS. By integrating the CSDS data into the HNN, we created learnable Boolean kSatisfiability logic variants based on the HORNSAT and RANMAXkSAT models. Figure 3 clearly demonstrated that the HNN-RANkSATRA model, with NC values ranging from 1 to 10, outperformed the HNN-HORNkSATRA and RANMAXkSATRA models in terms of RMSE. This superiority could be attributed to the utilization of random logical inconsistencies in HNN-RANkSATRA, which facilitated the determination of the optimal synaptic weight (SW) vector. The optimal SW vector played a crucial role in achieving optimal CSDS classification. The corresponding MAE values depicted in Figure 3 supported the RMSE results shown in Figure 2.

The assessment of model performance was divided into two main parts. Firstly, we evaluated the quality of solutions generated by different search techniques by considering the training errors. Secondly, we analyzed the robustness and efficiency of the proposed model by comparing the computational time (CT) and resources (Q) required to execute the model's mechanisms. The Performance Evaluation section provided a detailed analysis of five performance evaluation metrics used to assess the training and testing stages of our modified models. The main contribution of this research was to demonstrate the effectiveness of HNN in satisfiability logic, surpassing the performance of existing models.

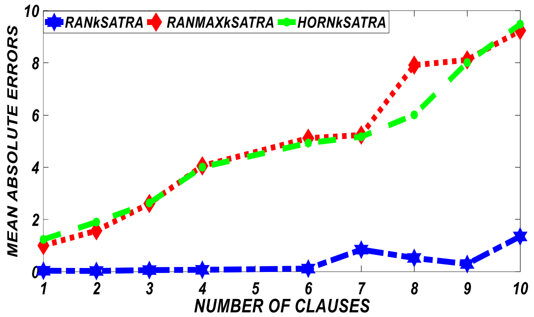

Figure 1: MAE evaluation of HNN models for CSDS classification

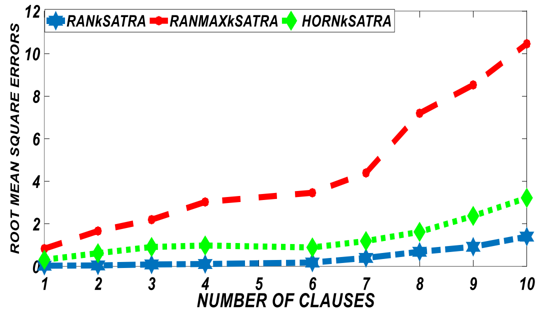

Figure 2: RMSE evaluation of HNN models for CSDS classification

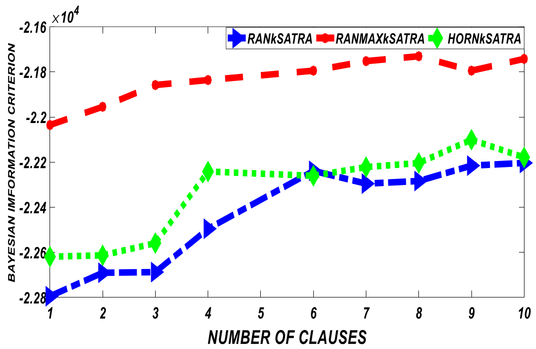

Figure 3: BIC evaluation of HNN models for CSDS classification

The evaluation of the proposed model reveals intriguing insights when comparing the Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Bayesian Information Criterion (BIC) values across different models. Figure 1 clearly illustrates that the HNN-RANkSATRA model achieves the lowest MAE values, particularly at NC = 2 with an MAE of 0.027. However, as NC increases to 10, the MAE also increases to 1.3515. The search process of HNN for HORNkSATRA and RANMAXkSATRA follows a similar trend, with RANMAXkSATRA exhibiting the highest error at NC = 8.

Figure 2 provides an overview of the RMSE performance trends for the HNN models, comparing RANkSATRA, RANMAXkSATRA, and HORNkSATRA. It is evident that at NC = 1, the RMSE value is 0.0323, while at NC = 10, it reaches 1.3995. These values are lower compared to HNN-HORNkSATRA and HNN-RANMAXkSATRA. Notably, HNN-RANMAXkSATRA records the highest RMSE, with 0.832 at NC = 1 and 10.4602 at NC = 10. The search process of HNN for RANkSATRA and HORNkSATRA follows a similar RMSE trend with minimal variation. As the value of NC increases, the complexity of the HNN models' learning process grows, as they need to search for consistent mappings to interpret the logical rules for optimal CSDS classification. However, the HNN demonstrates success in interpreting the existing logical rules (RANMAXkSATRA and HORNkSATRA) in some cases but gets caught in a trial-and-error search process, resulting in higher RMSE and MAE values. Consequently, the HNN accumulates more significant errors in interpreting the optimal representations for HORNkSATRA and RANMAXkSATRA. This pattern persists as the complexity of the HNN model increases. The training process of the HNN involves computationally demanding searches for possible representations of logical rules, leading to higher RMSE and MAE values. However, the proposed RANkSATRA method plays a crucial role in establishing optimal interpretations of the logical rules, facilitating the connection between occurrences and the decision-making process of the HNN in CSDS classification.
The performance of the HNN, as indicated by the MAE and RMSE values in Figure 1 and 2, is further supported by the BIC values presented in Figure 3. BIC serves as a criterion for selecting the "best" model that achieves a balance between under-fitting and overfitting the data. Although BIC aids in model selection, it does not provide a comprehensive assessment of the overall model quality. In this context, HNN-RANkSATRA proves to be the most favorable choice for CSDS classification, outperforming other models based on BIC. The inclusion of MSE in BIC computation tends to penalize the values, resulting in HNN exhibiting the lowest BIC when mapping the RANkSATRA logical rule.

Table 1. HNN Computational time

NC	RAN*k* SATRA	RANMAX*k* SATRA	HORN SATRA
1	0.643	1.8232	1.735
2	0.835	2.0279	2.8006
3	1.9707	5.3258	6.1323
4	3.2358	11.1566	13.004
6	9.7422	19.434	24.9292
7	18.46	22.5552	35.1675
8	25.2815	36.9081	42.005
9	37.958	65.6528	58.0088
10	72.312	91.4101	76.23457

Table 1 presents a comprehensive overview of the CPU timings for the learning and retrieval processes of the HNN when applied to the RANkSATRA logical rule, compared to the existing logical rule, for CSDS classification. These timings serve as an indicator of the models' resilience in logic mining. In general, when using a smaller NC, the HNN requires less CPU time and completes the learning and testing cycle for CSDS classification more quickly. However, as the complexity increases, the HNN-RANkSATRA model takes longer to complete the learning process.

Despite the increased complexity, the HNN demonstrates its effectiveness in reducing kSatisfiability inconsistencies and computing the global solution within a reasonable timeframe on the CPU. It is important to note that the CPU time consumed by the HNN for the RANMAXkSAT logical rule consistently exceeds that of the proposed RANkSATRA and the existing HORNSATRA logical rule. However, the CPU time recorded for the previous approaches was higher due to the additional iterations required to generate the optimal logical rule using the HNN.

The HNN's learning mechanism successfully identifies the optimal RANkSATRA logical rule to establish connections between attributes in the real CSDS dataset. The proposed RANkSATRA logical rule achieves an impressive accuracy of 92.1%, surpassing the accuracy of the existing logical rules being investigated, which achieve up to 80% accuracy in CSDS classification. In summary, the HNN demonstrates compatibility with RANkSATRA for learning and testing in CSDS classification, resulting in the lowest RMSE and MAE errors, as well as improved accuracy for a logical rule. Thus, the HNN-RANkSATRA logical rule shows promise in assisting the healthcare sector with CSDS categorization, outperforming other existing models in terms of minimal errors and efficient computational time.

CONCLUSION

This study successfully develops the HNN as an effective representation of the RANkSAT mechanism and integrates it into a logic-based reverse analysis framework within the HNN. This approach demonstrates its effectiveness in solving real-life datasets, particularly the Covid-19 dataset, by transforming it into an optimal logical mapping using the RANkSAT representation. This enables the identification of correlations between variables and accurate classification of Covid-19 instances as either "Detected" or "Not Detected."

However, a limitation of the HNN is its susceptibility to local solutions (premature convergence) instead of finding the global solution. To overcome this limitation, our future work will involve integrating advanced metaheuristic algorithms like Differential Evolution Algorithm (DEA), Election Algorithm (EA), Genetic Algorithm (GA), Dragonfly Algorithm (DA), among others, to enhance the performance of the HNN in the training and retrieval processes. This integration aims to prevent premature convergence and improve the searching and classification capabilities of the HNN. Additionally, we plan to explore other variants such as XOR-SAT, Random Half-SAT, MAX-kSAT, Random NAE-SAT and so on to address optimization problems more effectively. Furthermore, our future studies will extend the application of our approach to diverse datasets from various domains, including agriculture, finance, actuarial science, and the environment.

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